Set-based Multi-Sensor Data Fusion For Integrated Navigation Systems

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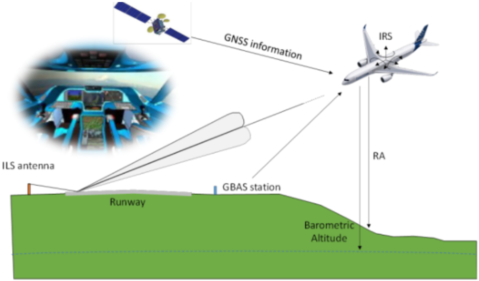
Outline of the Talk

1. Introduction
2. Multi-Sensor data fusion Architecture
3. Simulation Results
4. Conclusion & Further results

- **COCOTIER** (COncept de COckpit et Technologies Intégrées En Rupure, 2019-2022) is a collaborative project on new technologies for future intelligent cockpit in Single Pilot Operations (SPO, 2030+).
- The project is supported by the French Directorate General of Civil Aviation (DGAC) and coordinated by Airbus.
- Partners : 14 industrial and academic partners :
  - Industrial partners : Airbus (coordinator) – Dassault aviation – SAFRAN – Thales – ATR – Factem – OKTAL Synthetic Environment – Ratier Figeac – Vodea – Zodiac Aero Electric.
  - Academic partners : IMS Lab (U-Bordeaux) – LAAS-CNRS (Toulouse) – LEAD Lab (Toulouse) – ONERA (French Aerospace Lab) – ENAC (French Civil Aviation University).



- **Objective** : Provide precise Aircraft Position in runway frame.

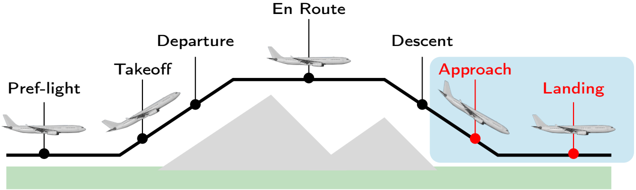


Figure – Different stages of a flight.

- **Inputs** :
  - Used for data fusion :
    - Inertial Reference System (IRS) (3D velocity).
    - Global Positioning System (GPS)(3D position).
    - Instrument Landing System (ILS) (lateral and vertical angular deviations).
  - Used as reference : Differential GPS (DGPS)
- **Outputs** : Position $(X_{RWY}, Y_{RWY}, Z_{RWY})$.

- IRS considered as the reference sensor $\rightarrow$ Generally consolidated using dedicated on-board processing.
- Measured IRS velocity v_k :

$$v_k = v_k^0 + E_k \omega_k \tag{1}$$

v_k^0 : Actual aircraft 3D velocity.
E_k : Time-varying matrix characterising the measurement noise ω_k.

- Aircraft 3D position vector $x_k = [X_k \; Y_k \; Z_k]^T$:

$$x_{k+1} = x_k + T_s(v_k^0 + E_k \omega_k) \tag{2}$$

T_s : Sampling time.

Problem Statement

- GPS : 3D position.
- ILS : aircraft vertical and lateral deviations.
  - Localizer (η_{LOC}).
  - Glideslope (η_{GS}).

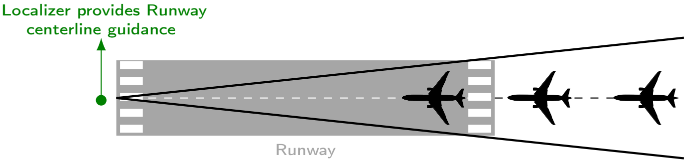


Figure – Localizer representation.

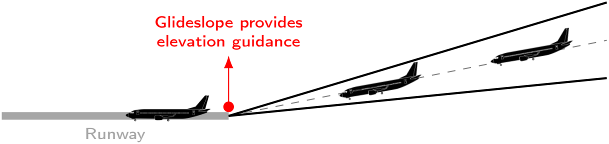


Figure – Glideslope representation.

- Global measurement model :

$$y_k = \begin{bmatrix} y_k^1 \\ y_k^2 \end{bmatrix} = h(x_k) + \underbrace{\begin{bmatrix} F_k^1 & 0 \\ 0 & F_k^2 \end{bmatrix}}_{F_k} \underbrace{\begin{bmatrix} \vartheta_k^1 \\ \vartheta_k^2 \end{bmatrix}}_{\vartheta_k} \tag{3}$$

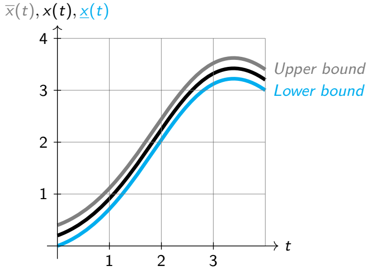
y_k^1 and y_k^2 : GPS position and ILS deviations measurements, respectively.

- The observation function $h(.)$ relates both measurements with the state vector x_k :

$$h(x_k) = \begin{pmatrix} X_k \\ Y_k \\ Z_k \\ \frac{\left(Y_k - d_{offset} - (L - X_k) sin(b_{align})\right) L}{s(L - X_k)} \\ tan^{-1}\left(\frac{TCH - Z_k}{X_k}\right) - GPA \end{pmatrix} \tag{4}$$

F_k^1 and F_k^2 characterise the GPS and ILS measurement noise ϑ_k^1 and ϑ_k^2.

- Multi-sensor data fusion using Kalman-like filtering (prediction+update).
- How to characterize ω_k and ϑ_k ? Noise covariances may be difficult to obtain.
- Set-membership does not require any assumption about the probability distributions and rely on unknown-but-bounded uncertainties.



- Set-based data fusion $\rightarrow$ Extended Zonotopic Kalman Filter (EZKF).
- Normalized uncertainties are assumed to be bounded by a unit hypercube expressed as a zero-centered zonotope :

$$\omega_k \in \langle 0,\ I_{n_x} \rangle, \quad \vartheta_k \in \langle 0,\ I_{n_y} \rangle \tag{5}$$

  I_{n_x} and I_{n_y} are identity matrices.

- Online tuning/adaption of E_k and F_k (state and meas. noise bounds).

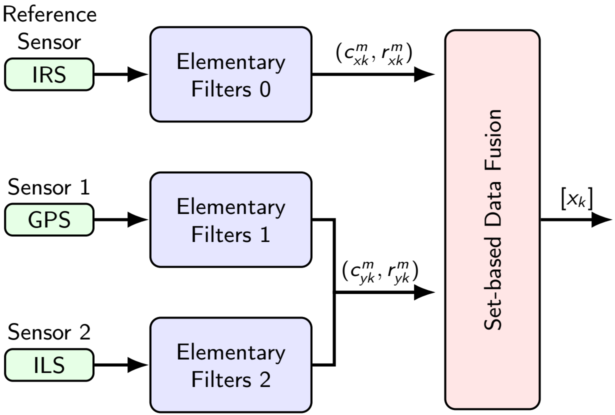


Figure – Set-based navigation sensor fusion scheme.

- Extraction of features and useful infor. from **each scalar** preprocessed signal :
- Basic (first order) learned/tuned model + First order interval-based algorithm.
- Structure inspired by a ZKF [1] optimizing a 1-norm criterion.

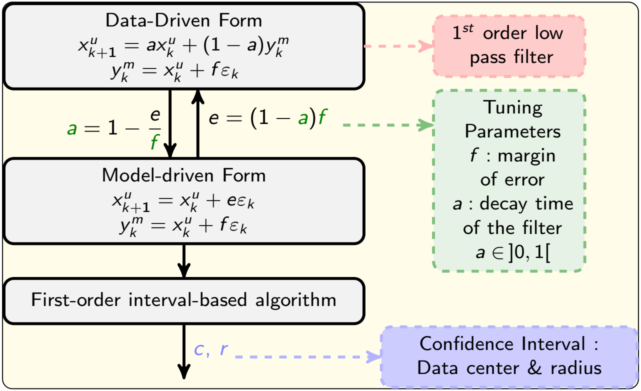


Figure – Elementary Filter's layout.

1. Christophe Combastel. Zonotopes and kalman observers : Gain opti-mality under distinct uncertainty paradigms and robust convergence.Automatica, 55 :265–273, 2015

Algorithm 1: Simplified 1-norm based scalar ZKF as used in the bank of elementary filters.

Input: a, f and y_k^m
Output: c_k^m and r_k^m
Initialize: $c_k^u \Longleftarrow c_0^u$, $r_k^u \Longleftarrow r_0^u$

for $k = 1$ **to** N **do**
  if $r_k^u < f$ **then**
    $\gamma_k = a$
  else
    $\gamma_k = 0$
  end if
  $c_{k+1}^u = \gamma_k c_k^u + (1 - \gamma_k) y_k^m$
  $r_{k+1}^u = pos(|y_k^m - c_k^u| - f) + a.min(r_k^u, f)$
  $c_k^m = c_k^u$
  $r_k^m = r_k^u + f$

Set-based data fusion

- IRS/GPS/ILS measurement model (with ILS nonlinearities) :

$$y_k = h(x_k) + F_k \vartheta_k$$

- The observation function $h(.)$ is approximated, for $x_k = c_k + \delta_k$ with $\delta_k \in [\delta_k] = (0 \pm r_k)$, as follows :

Jacobian matrix of $h(.)$
evaluated at c_k

$$h(c_k + \delta_k) = h(c_k) + \mathbf{L}h(c_k) \cdot \delta_k + \mathbf{R}_1 h(c_k, \delta_k)$$

Remainder of the first-order
Taylor development to be enclosed

- After some calculation, the following inclusion holds :

$$h(c_k + \delta_k) \in h(c_k) + \mathbf{L}h(c_k)\delta_k + (c_{hk} \pm r_{hk})$$

where c_{hk} and r_{hk} are the center and radius of the interval enclosing the remainder term.

- After some developments,

$$y_k = \mathcal{C}_k x_k + \hat{F}_k \hat{\vartheta}_k + u_k, \quad \hat{\vartheta}_k \in \langle 0, I_{n_y} \rangle \tag{6}$$

where

$$\mathcal{C}_k = \mathbf{L}h(c_k) \tag{7a}$$

$$\hat{F}_k \hat{\vartheta}_k \in 0 \pm r_h k + F_k \vartheta_k \tag{7b}$$

$$u_k = h(c_k) - \mathbf{L}h(c_k) c_k + c_{h\,k} \tag{7c}$$

- Data fusion based on an Extension of ZKF [2].
- In the proposed design, the time-varying matrices E_k and F_k are updated in real-time using the information processed by the elementary filters :

$$E_k = diag(r_{xk}^m) \tag{8a}$$

$$F_k = diag(r_{yk}^m) \tag{8b}$$

2. Christophe Combastel. Zonotopes and kalman observers : Gain optimality under distinct uncertainty paradigms and robust convergence.Automatica, 55 :265–273, 2015

Algorithm 2: Dedicated EZKF Algorithm.

Input: c^m_{xk}, r^m_{xk}, c^m_{yk} and r^m_{yk}

Output: $\underline{x}_k$ and $\overline{x}_k$

Initialize: $c_k \Longleftarrow c_0,\ H_k \Longleftarrow H_0$

for $k = 1$ **to** N **do**

/* Compute reduced zonotope */

$\overline{H}_k = \downarrow_q H_k$

/* Compute Jacobian matrix $\mathcal{C}_k$ */

$\mathcal{C}_k = \mathbf{L}h(c_k)$

/* Compute time varying matrices E_k, $\hat{F}_k$, P_k and Q_k */

$E_k = diag(r^m_{xk})$

$\hat{F}_k = diag\left(r_{h\,k} + r^m_{yk}\right)$

$P_k = \overline{H}_k \overline{H}_k^T,\quad Q_k = \hat{F}_k \hat{F}_k^T$

/* Compute the optimal filter gain */

$G_k = P_k \mathcal{C}_k^T \left(\mathcal{C}_k P_k \mathcal{C}_k^T + Q_k\right)^{-1}$

/* Compute the center and generator matrix of the zonotope $\mathcal{Z}_k$ */

$c_{k+1} = (I_{n_x} - G_k \mathcal{C}_k) c_k + T_s c^m_{xk} + G_k (c^m_{yk} - u_k)$

$H_{k+1} = \left[(I_{n_x} - G_k \mathcal{C}_k)\overline{H}_k,\ \ T_s E_k,\ \ -G_k \hat{F}_k\right]$

/* Compute the interval hull of $\mathcal{Z}_k = \langle c_k,\ H_k \rangle$ */

$\Box \mathcal{Z}_{k+1} = \langle c_{k+1}, |H_{k+1}|\mathbf{1} \rangle$

/* Compute the upper and lower bounds of fused data */

$$\begin{aligned} \overline{x}_{k+1} &= c_{k+1} + |H_{k+1}|\mathbf{1} \\ \underline{x}_{k+1} &= c_{k+1} - |H_{k+1}|\mathbf{1} \end{aligned}$$

- Tuning parameters inputs :
  - IRS, GPS and ILS margin of errors, f_x and f_y,

$$f_x = \begin{bmatrix} 0.1087 \\ 0.4052 \\ 0.1589 \end{bmatrix}, \quad f_y = \begin{bmatrix} 45.3618 \\ 35.5192 \\ 4.1909 \\ 0.1625 \\ 6.3898 \end{bmatrix}$$

- Simulation based on real data provided by Airbus : Scenario 1

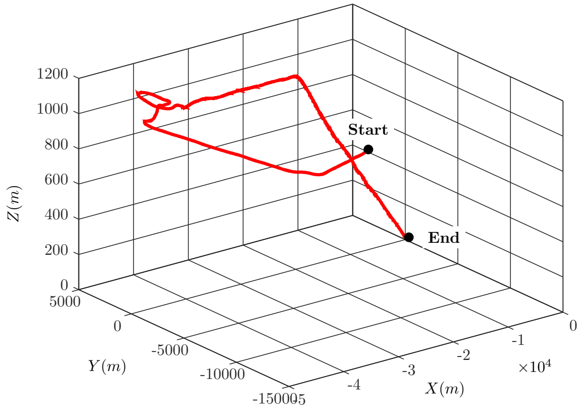


Figure – 3-D Trajectory of landing scenario 1.

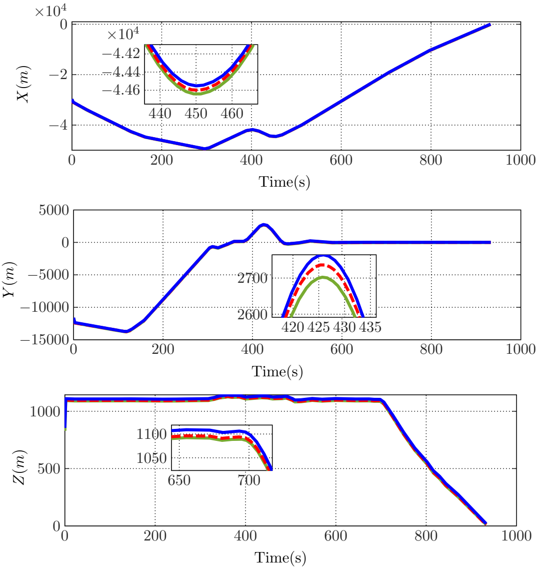


Figure – Interval Estimation of positions along x-, y- and z-axis for Scenario 1.

- Simulation based on real data provided by Airbus : Scenario 2

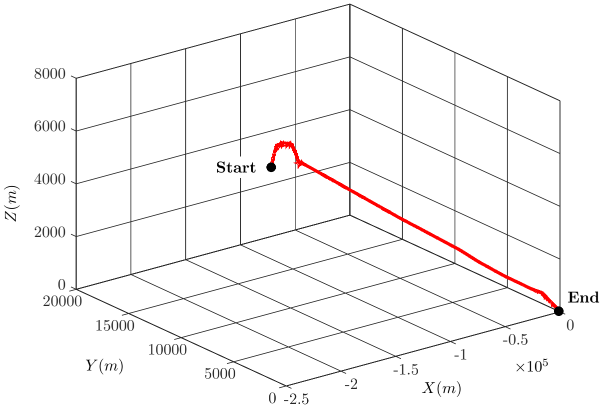


Figure – 3-D Trajectory of landing scenario 2.

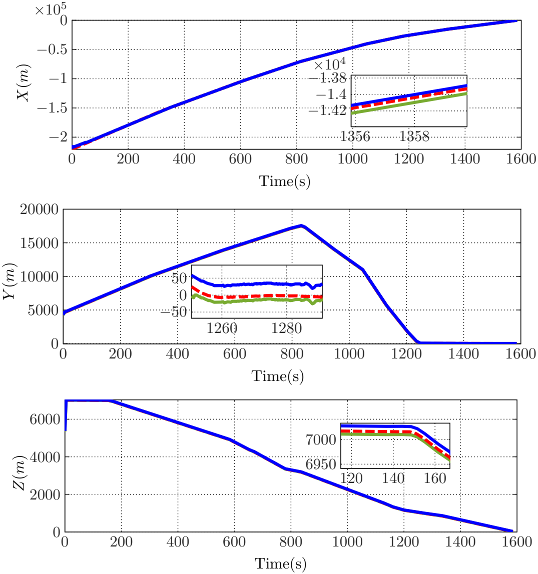
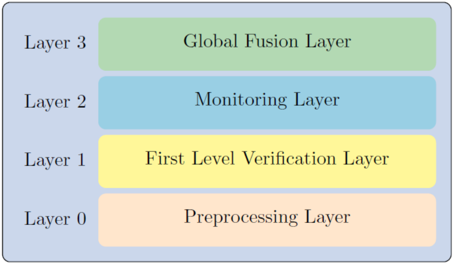


Figure – Interval Estimation of positions along x-, y- and z-axis for Scenario 2.

- **Conclusion**
  - IRS/GPS/ILS set-based multi-Sensor data fusion.
  - Extended zonotopic Kalman filter enclosing ILS nonlinearities.
  - Simulation experiments based on real flight data provided by Airbus.
- **Further results** [3]
  - Fault-tolerant issues and merging set-membership and probabilistic paradigms.
  - Further extensive simulations.
  - Layered data-fusion architecture.



3. S. Ifqir, C. Combastel, A. Zolghadri, G. Alcalay, P. Goupil, S. Merlet, Fault tolerant multi-sensor data fusion for autonomous navigation in future civil aviation operations, Control Engineering Practice, Volume 123, 2022. https://doi.org/10.1016/j.conengprac.2022.105132.